Evaluating the Implementation of New Services Models in the Financial Advisory Industry:

A Statistical Data Mining and System Dynamics Approach

by

Hugo Botelho Barra

B.S., Electrical Engineering and Computer Science
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Massachusetts Institute of Technology (2000)

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Author___________________
Department of Electrical Engineering and Computer Science
May 23, 1998

Certified by___________________
Gabriel R. Bitran
Nippon Telephone and Telegraph Professor of Management, Deputy Dean
Thesis Supervisor

Accepted by___________________
Arthur C. Smith
Chairman, Department Committee on Graduate Theses

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Abstract:

Program Alpha is a new business practice model designed to increase service quality and productivity of one of the world's largest financial services organizations, by implementing structured time management and a disciplined client and prospect contract process. This thesis quantitatively and qualitatively evaluates business impact of this program, by developing and applying two analytical frameworks. We first present and develop a System Dynamics framework for interpretation of qualitative information collected through interviews, focus groups and surveys, which measure the impact of Program Alpha from operational, organizational and behavioral perspectives. Secondly, we present a Statistical Data Mining framework for interpretation of quantitative financial and customer preference information. Using this framework, we generate a preliminary set of algorithmic guidelines for improvement of Program Alpha in future deployment stages. Such guidelines, based on statistical learning algorithms applied to historical data, aim to streamline the client segmentation process at the core of Program Alpha.

Thesis Supervisor: Gabriel R. Bitran
Title: Nippon Telephone and Telegraph Professor of Management, Deputy Dean

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To my family:

Leonor, Lionel and Cristina.

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Chapter 1
Introduction

1.1 Thesis Objective

The development of this thesis is part of a collaborative project between the MIT Sloan School of Management and a leading company in the financial advisory services industry, identified here simply as IBPCG (a fictitious name), for confidentially reasons. The various objectives of this project revolve around assessment of a new IBPCG program designed to profoundly modify and evolve the firm's service delivery model worldwide.

IBPCG is a successful full-services firm in the private client industry engaged in all aspects of the investment process, from initial decision through execution and follow-up. Using a financial advisor (FA) as a client's contact point, IBPCG recommends investment opportunities, provides research reports, executes trades, offers customer service support, and issues monthly reporting statements.

Program Alpha is a new business practice model designed to increase service quality and productivity of IBPCG financial advisors by implementing structured time management and a disciplined client and prospect contact process. The program has been implemented and is being rolled in select regions across the United States.

The overall project jointly carried by the MIT Sloan School of Management and IBPCG has two goals in evaluating the effectiveness of Program Alpha.

First, to evaluate whether the Program Alpha is effective in improving service delivery, by measuring the business impact of Program Alpha on the behavior of clients with specific regard to their assets invested at IBPCG and their satisfaction with IBPCG's service, as well as the impact of Program Alpha on the behavior of financial advisors with regard to their productivity.

Second, to determine possible improvements to various aspects of the program's implementation, as well as its target environment, at operational and strategic levels, prior to its national roll-out.

This thesis focuses on specific analytical and technical aspects of the effectiveness evaluation and improvement suggestion processes.

1.2 Thesis Structure

This thesis contains three core components that are part of the full Program Alpha evaluation project carried out by the MIT Sloan School of Management team for IBPCG[1]. These three, semi-independent analytical modules share the same data sets but focus on separate sub-areas of the evaluation process.

Chapter 2 presents statistical quantitative and qualitative analyses performed respectively on financial measurements and data from surveys conducted with FAs and clients after Program Alpha implementation. The findings from these analyses shed initial light into results and perceptions generated as a consequence of the new program, and serve as inputs to the analytical frameworks developed in Chapters 3 and 4.

Chapter 3 presents an introductory analytical framework based on System Dynamics for interpretation of qualitative data collected through focus groups, management interviews and telephone surveys. The objective of this approach is to explore first- and second-order effects of implementation of Program Alpha throughout several districts, from operational, behavioral and organizational points of view. Several models are introduced, aimed at enhancing the understanding of dynamic complexity, by exploring the impacts of indirect relationships between elements of the system and time-delayed effects of the implementation.

Chapter 4 presents a statistical Data Mining framework and methodology for creating a classification algorithm that allows FAs to partition their book of clients into three separate groups: clients that to be kept within the FA's book, clients that will be transferred to another FA not enrolled in Program Alpha, or clients that will be transferred to IBPCG's non-dedicated call center-based advisory division.

[1] Full project report: Bassim Halaby and Qunmei Li, "Introducing Fundamental Changes to a Service Delivery Model: 'Lessons from a Financial Advisory Organization'," MIT Master Thesis, 2002.

1.3 Description of Program Alpha

As essential background, it is important to describe the change process that the Private Client group within IBPCG has been undergoing for the past 4 years. Over the last decade, to briefly summarize the relevant course of events, IBPCG has gone from being an undisputable leader provider of comprehensive wealth management services with distinguished and unparalleled breadth and a high level of customization to a provider of near-commoditized financial advisory services. In order to recover the edge lost to some of its largest competitors, IBPCG's management decided to re-tool its financial services advisory team (composed of over 10,000 financial advisors) with a new methodology for recruiting and serving clients. That methodology – referred to here as *Program Alpha* for confidentiality purposes – was first implemented with two pilot groups of about 100 financial advisors (FAs) in 1999 and 2000.

Program Alpha essentially consists of enforcing a book size limit (i.e. maximum number of clients served) to all FAs, such that the quality of service provided to each individual client can be matched to a firm-wide standard. With a limited number of clients, it is possible to ensure a certain level of individualized attention of the FA and time dedication to each client, which is also explicitly specified by Program Alpha. One of the principal challenges to implementation of the program has been the "segmentation" process, which is essentially the task of selecting which clients to maintain in an FA's book and which clients to transfer to a different FA (not 'enrolled' in Program Alpha) or to IBPCG's call center-based, non-dedicated service center.

Chapter 2

Quantitative and Qualitative Statistical Analysis

In this chapter, analysis and results of the surveys carried out to evaluate Program Alpha are presented. Various statistical methods were employed to perform both quantitative and qualitative analyses of financial measurements and surveys conducted with FAs, CAs and clients. A summary of findings is presented at the end of the section.

2.1 Statistical Research Methodology

Two main sets of analyses were performed based on data obtained for Program Alpha implementation over the period August/2000 to December/2001: quantitative analysis of business metrics and qualitative analysis of attitudinal effects.

2.1.1 Quantitative Methodology

The first analysis performed in this study was led by the Management Science team at IBPCG in cooperation with the MIT team and consisted primarily of the quantitative analysis of financial data and other hard metrics from Program Alpha. This data was obtained directly from the internal systems and did not require development of any specific data collection vehicle, with the exception of a short e-mail questionnaire that allowed for a fine classification of financial advisors in terms of their adoption level of Program Alpha.

The principal objectives of the quantitative analysis were measuring business impact of Program Alpha on the behavior of households with specific regard to assets with IBPCG and investment activity profile, as well as assessing the business impact of the program over the behavior of financial advisors with specific regard to characteristics of their book.

In both cases, a comparative analysis was performed in order to observe the differences in behavior between households and financial advisors who were part of Program Alpha and those who were not part of the program.

Business impact measures at the client level are:

1. Total assets
2. PCs
3. Margin usage
4. Client satisfaction
5. Annuitized assets
6. Asset allocation
7. Investment performance
8. Velocity (PCs / Assets)

FA productivity measures to be examined at the post-split and pool level are:

1. Total assets
2. PCs
4. Margin usage
5. Client satisfaction
6. Retention
7. New households / accounts
8. Annuitized assets
9. Asset allocation
10. Investment performance
11. Velocity (PCs / Assets)
12. Households in various asset tiers
13. Book size

2.1.2 Qualitative Methodology

The second analysis performed in this study was conducted jointly by the Market Research team at IBPCG and the MIT team. It consisted mainly of measuring the attitudinal impact of Program Alpha on FAs, CAs and clients themselves. Contrary to the quantitative analysis previously described, this task entailed a broader set of soft factors and fewer hard metrics, and no preliminary data was available from an internal system. Certain data collection vehicles were used, including individual interviews, focus groups, and telephone questionnaires.

2.1.2.1 Individual Interviews

Individual interviews were conducted with a variety of individuals, including corporate management (headquarters), complex managers, branch managers, FAs, CAs and IT managers. Despite the statistical insignificance of the opinions and visions collected, a number of valuable insights were obtained and later matched with results from questionnaires. There was no specific format or structure created for these interviews and a number of them were conducted informally. Records of these interviews have not been included as part of this paper.

2.1.2.2 Focus Groups

Focus groups were run with the primary objective of assisting the crafting and fine-tuning of the telephone questionnaires. The goal was to create an environment for FAs and CAs to interact with each other and openly discuss some of their common issues and difficulties in a reserved forum. Those discussions would ideally have begun to point out evidence of key gaps in the Program Alpha implementation.

The structure of the focus groups was very carefully planned and scripted. The discussions themselves were mediated by a professional from the field who used questions from the script and steered the conversations through various relevant topics, some of which were not emphasized in the original script but gained importance during the discussions. Each focus group discussion took an average of 1.5 hours.

In total, six focus groups were conducted, including three with FAs and three with CAs. The meetings took place in 3 different cities and included a mix of FAs working 'solo' or in teams. A detailed record of these discussions has not been included as part of this thesis document for confidentiality reasons, but it is available to authorized parties upon request.

2.1.2.3 Questionnaires

Telephone questionnaires were conducted with 69 FAs implementing Program Alpha, as well as 400 of their clients. The primary objective of this research tool was to collect statistically relevant data on their behavior after the initial roll-out of Program Alpha.

Initially, the research team planned to conduct interviews through telephone questionnaires with the following:

a) Financial advisors that were in the process of implementing Program Alpha;
b) Financial advisors who had begun to implement and then decided to drop out of Program Alpha;
c) Client associates who worked with financial advisors that were in the process of implementing Program Alpha;
d) Clients of financial advisors that were in the process of implementing Program Alpha.

Due to time and resource constraints, the research team decided that only questionnaires (a) and (d) would be finalized and actually conducted. This decision greatly diminished the potential impact of this research tool, especially because some of the most relevant results were expected to come from (b), i.e. telephone interviews with financial advisors who had decided not to continue in Program Alpha. Their rationale for dropping out of the program would likely generate substantial insight into some of the gaps in the entire initiative.

Questionnaires were given through telephone interviews conducted by an independent firm. Each FA interview had on average 40 questions and lasted about 45 minutes. Each client interview had on average 50 questions and lasted about one hour.

Copies of the questionnaires developed for FAs and clients have not been included as part of this thesis document for confidentiality reasons, but are available to authorized parties upon request.

2.2 Quantitative Analysis

Information on this section was extracted from reports put together by the Management Science group at IBPCG supported by the MIT team.

2.2.1 Summary of Test-Control Group Analysis

The test group of Program Alpha FAs consists of 75 FAs who attended the first Program Alpha training program in the Midwest district held in August 2000. The control group of non-Program Alpha FAs consists of 828 FAs who were selected to match the test group based on geographic region, PC quintile, book size, and total assets. Both groups were tracked over a 12-month period before the Program Alpha training (Aug 99 – Jul 00) and a 14-month period afterwards (Nov 00 – Dec 01).

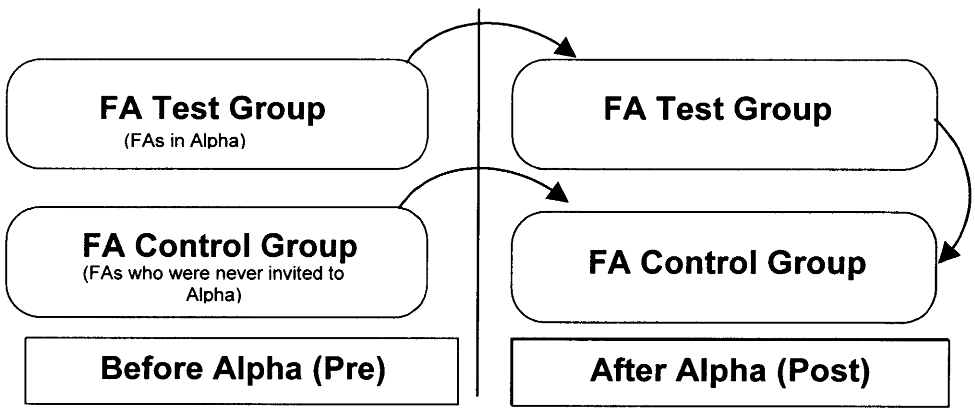


Figure 1: Test group and control group of FA

The test group of Program Alpha clients consisted of 16,374 clients associated with the 75 FAs who attended the first Program Alpha training program in the Midwest district held in August 2000. The control group of non-Program Alpha clients consisted of 16,364 clients associated with the 828 control group FAs. These clients were randomly selected to match the Program Alpha clients based on geographic region, assets, and PCs.

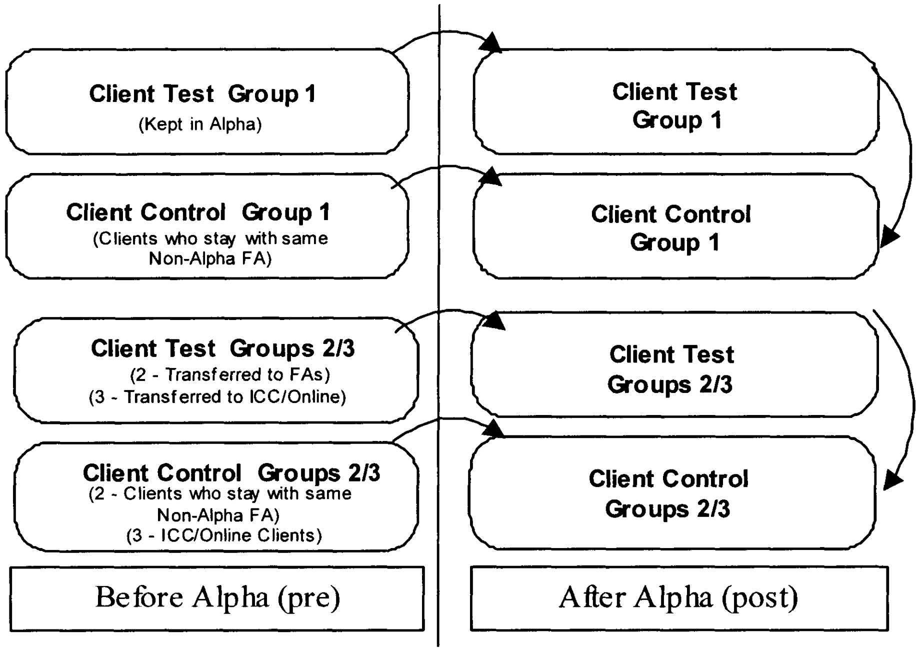


Figure 2: Test group and control group for clients

Both groups were tracked over a 12-month period before the Program Alpha training (Aug 99 – Jul 00) and a 14-month period afterwards (Nov 00 – Dec 01). A similar approach was used to evaluate the 1,415 clients (associated with the 75 Program Alpha FAs) who were transferred to a different FA and the 6,800 clients who migrated to ICC.

2.2.2 Quantitative Findings

2.2.2.1 Summary of Financial Advisor Quantitative Findings

Table 1 displays productivity measures where the Program Alpha FAs had a statistically significant change vs. the control group.

FA Productivity Measure	Direction of Change
PCs	Better (Higher)
Velocity	Better (Higher)
Market Error Dollars	Better (Lower)
Book size	Better (Lower)
Annuitized Assets	Worse (Lower)
New Households Acquired	Worse (Lower)
Client Satisfaction with CA Service	Better (Higher)
% of Clients who feel they need more FA Contact	Better (Lower)
% of Clients who feel FA is working in their best interest	Better (Higher)

Table 1: Productivity measures

No statistically significant change was found in total assets, client retention or asset allocation.

The subset of FAs who self-assigned themselves as strong Program Alpha implementers did slightly better than the total Program Alpha group in velocity and market error dollars. Table 2 summarizes selected results:

FA Productivity Measure	Group	Pre-Program Alpha Mean / FA	Post-Program Alpha Mean / FA	Change from Pre to Post Program Alpha			
				Change	% Change	Lift	% Lift
PCs ($K) (Annual)	Test	$526K	$532K	$5K	1.0%	$40K	7%
	Control	$552K	$516K	-$35K	-6.4%		
Velocity (bps)	Test	74.0	81.3	7.4	10.0%	6.1 *	8% *
	Control	75.3	76.5	1.3	1.7%		
Book size	Test	289	208	-81	-28%	-31	-11%
	Control	289	239	–50	-17%		
Annuitized Assets ($M)	Test	$33M	$28M	-$5M	-15%	-$4M	-8%
	Control	$12M	$12M	-$1M	-7%		
CA Service (Performance Report 1-7 scale)	Test	6.16	6.29	0.13	2.1%	0.11	2%
	Control	6.26	6.28	0.02	0.3%		
Rate of Return (Annual %)	Test	6.4%	-10.0%	-16.4 pts	N/A	-2 pts	N/A
	Control	5.4%	-9.0%	-14.4 pts	N/A		
Market Errors ($K) (annual)	Test	$3.6K	$0.8K	-$2.8K	-76.7%	-$2.0K*	-54%*
	Control	$3.0K	$2.3K	-$0.7K	-23.2%		

*Indicates this lift was significant only at the 90% confidence level

Table 2: Selected results of FA's self-assignment

2.2.2.2 Summary of Client Quantitative Findings

The following table displays productivity measures where the Program Alpha clients had a statistically significant change vs. the control group.

FA Productivity Measure	Direction of Change
Assets	Better (Higher)
PCs	Better (Higher)
Velocity	Better (Higher)
% of Clients who feel FA needs to provide more research	Worse (Higher)

Table 3: Productivity measures from clients under Program Alpha

No statistically significant change was found in client retention, annuitized assets, margin usage, and market errors. Clients who were transferred to a non-Program Alpha FA or to Investor Call Center (ICC) generally did not show any significant negative behavior.

The following table summarizes selected results for Program Alpha clients:

Client Performance Measure	**Group**	**Pre-Program Alpha Mean / HH**	**Post-Program Alpha Mean / HH**	**Change from Pre to Post Program Alpha**			
				Change	**% Change**	**Lift**	**% Lift**
Total Assets ($K)	Test	$370K	$333K	-$37K	-10%	$11K	3%
	Control	$376K	$328K	-$48K	-13%		
PCs ($) (Annual)	Test	$2079	$1947	-$132	-6%	$299	13%
	Control	$2289	$1858	-$431	-19%		
Velocity (bps)	Test	77	78	1	1%	9	11%
	Control	84	76	–8	-10%		
Rate of Return (Annual %)	Test	9.4%	-10.7%	-20.1 pts	N/A	-0.9 pts*	N/A
	Control	9.2%	-10.0%	-19.2 pts	N/A		

* Indicates this lift was significant only at the 90% confidence level

Table 4: Client performance measures for Program Alpha

In light of the results displayed above, from the point of view of analyzing the effectiveness of Program Alpha, this quantitative analysis is not very conclusive. As discussed in the next chapter of this thesis, Program Alpha did not create all the necessary conditions for generating marked business impact in the short- or mid-term, but instead started to set up a new framework for improved service delivery.

In addition to that, the time horizon of observation and data collection used for this evaluation project is not sufficiently long, especially in light of the market turmoil that was recently faced by investors and financial advisors.

In this scenario, where financial measures have not proved useful to evaluate effectiveness of Program Alpha, qualitative analysis of attitudinal impact caused by implementation of the program may become a component of very important value. This is the subject of the next section.

2.3 Qualitative Analysis

The analysis of qualitative data based on interviews, focus groups and telephone questionnaire was performed based on data gathered from interviews, focus groups and preliminary interpretation of questionnaire results. The results from this phase are presented in this section.

2.3.1 Qualitative Findings

2.3.1.1 Focus Groups and Interview Findings

The following insights and observations were drawn from focus group discussions and personal interviews conducted with branch managers, IT managers, and other individuals at the complex and corporate levels.

- Financial advisors and client associates endorse the Program Alpha theory. Generally speaking, the disciplined approach to reducing the client base and improved communication scheme with remaining high-net-worth clients is very well regarded as a positive business growth driver.
- Consistent problems exist related to Program Alpha roll-out from a systems standpoint, which have hampered full program implementation. These include inflexibility of the schedule calendar, lack of data portability and networking capability, absence of note entry, difficulty in customizing report content, and slow printing of client information for folders. As a result, FAs and CAs are not implementing the full potential of Program Alpha and frequently make use of

other software packages or customize their approach to fit the limitations of technology already mastered.

- There are notable differences between offices in terms of level of implementation of Program Alpha and user satisfaction with the program. Implementation seems more complete in the Kansas City office where concentrated motivational and support efforts were in place after the initial training session. In contrast, Program Alpha users in Boston and Indianapolis note an absence of concentrated follow-up at the office level, including limitations on client associate staffing in Indianapolis.
- All FAs in this sample have undertaken client classification and client migration via Program Alpha and acknowledge the value of the program in this regard. While they subscribe to the 12/4/2 model as an ideal target and for its disciplinary value, FAs note that the model must be tailored to client needs.
- Many FAs, especially in the Kansas City complex, strongly rely on the CAs as 'schedule enforcers'.
- Program Alpha users have not yet progressed to the 'acquisition' phase of the program in an organized manner, although they do support the 'smart marketing' approach to generating referrals. To date, FAs have generally experienced success in asset consolidation, based on more regular client contact. Other positive Program Alpha effects, particularly in Kansas City, include higher internal performance scores and greater job satisfaction including reassurance that client issues are receiving proper attention.
- Non-users of Program Alpha are perceived (by users) as:
  - Older, more technology-resistant or less interested in business growth;
  - Reluctant to undertake client migration;
  - Unwilling to invest the time needed to implement the program.
- There is also some indication that teams may be better in a better position to implement Program Alpha, including assignment of the burden of organizational responsibility to one CA. However, users note that all FAs on a team must be involved with Program Alpha to the same extent, in order to ensure successful implementation.

2.3.1.2 Financial Advisor Questionnaire Findings

Financial advisor perception of Program Alpha value: FAs generally support Program Alpha strongly and believe it is a highly beneficial program to IBPCG's business. FAs also profoundly buy into quite the concepts of segmentation and 12/4/2. The following tables show a summary of relevant statistical results on this topic:

- High satisfaction with program;
- High perceived program value overall;
- High willingness to continue participating in program.

	Extremely Positive	Positive
Overall with program	48%	48%
Valuable to clients	46%	45%
Valuable to FAs	51%	41%
Valuable to CAs	41%	38%
Valuable to IBPCG	57%	33%
Will you continue to participate	88%	9%

Table 5: Financial advisor perception of Program Alpha value – Part 1

- High perceived value in segmentation and 12/4/2 contact schedule.

Specific features:	Extremely Valuable	Valuable
Reducing book size	46%	23%
Segmenting Client base	45%	35%
12-4-2 contact schedule	52%	33%

Table 6: Financial advisor perception of Program Alpha value – Part 2

- High perceived program value for client retention;
- High perceived program value for attracting new assets from existing clients.

Perceived Efficiency:	Extremely Valuable	Valuable
Increasing your overall efficiency in running your	42%	42%
Increasing the number of IBPCG's products and services used by HNW clients	17%	33%
Attracting HNW clients	30%	52%
Attracting assets of existing clients	35%	51%
Increasing the number of client Referrals	32%	42%
Retaining clients	60%	40%
Providing high-quality service to clients	51%	35%

Table 7: Financial advisor perception of Program Alpha value – Part 3

- Perceived adequacy of 12/4/2 schedule for 'A-Class' clients.

	Too Many	Not Enough	Just right	Don't Know
# of calls (12)	16%	3%	76%	4%
# of portfolio reviews (4)	22%	3%	74%	1%
# in-person meetings (2)	12%	15%	73%	1%

Table 8: Financial advisor perception of Program Alpha value – Part 4

Financial advisor perception of Program Alpha tools: Desired improvements for specific operational tools that support the system. The tools themselves suggest that improvements are possible. Apart from the Initial Segmentation Report which is viewed as at least valuable by 78%+ of respondents, the scoreboard received mixed scores, while the folder system and client contact software was considered not very adequate by a significant number of respondents. Many have either modified the folder system and/or using non- IBPCG software to assist them with following the program. The following tables show a summary of relevant statistical results on this topic:

- High perceived value in folder system;
- High perceived value in Initial Segmentation Report;
- Low perceived value in Scoreboard.

	Extremely Valuable	Valuable
Creating client folders	33%	29%
Using Scoreboard	3%	26%
Initial Report to segment client base	39%	39%

Table 9: Financial advisor perception of Program Alpha tools – Part 1

- Very low standardization on software used by financial advisors for Program Alpha.

IBPCG software designed for Program Alpha	50%
Other IBPCG software	4%
Software you have developed	15%
Non-IBPCG software	39%

Table 10: Financial advisor perception of Program Alpha tools – Part 2

- High level of adoption of folder system;
- Most folder system users have modified the system to fit own needs.

	YES	NO
Are you using the folder system?	70%	30%
Are you using a modified version of the folder	86%	14%

Table 11: Financial advisor perception of Program Alpha tools – Part 3

2.3.1.3 Client Questionnaire Findings

Client perception of service level under Program Alpha: Clients of Program Alpha FAs generally feel that the quality of services provided by IBPCG is high, even in comparison with other firms and are satisfied with the services provided by their FA. They seem, however, to have come to expect this level of quality, which meets but does not greatly exceed their requirements and represents good, but not exceptional, value for their money. Their satisfaction with the service contrasts with the low performance of their investments compared to expectations. The following table shows a summary of relevant statistical results on this topic:

- High level of adoption of folder system;
- Most folder system users have modified the system to fit own needs.

Specific features:	Extremely positive	Positive
Quality of Service (High/low)	27%	52%
Satisfied w services	38%	43%
Comparison w other firms	16%	44%
Responsiveness in correcting problems (58 answers)	14%	17%
Service vs requirements	16%	14%
Performance of investment compared to expectations	3%	5%
Value for money of service and products	19%	37%

Table 12: Client perception of service level under Program Alpha

Perception of frequency of contacts by financial advisor (and team): Most clients have not noticed a significant difference in their contact schedule by the FA. The following table shows a summary of relevant statistical results on this topic:

- Most clients have not noticed a change in the frequency of contact.

	Increased	Decreased	Same
Frequency of contact from FA or FA team	18%	15%	53%
Frequency of contact from CA	13%	10%	56%
Frequency of portfolio reviews	9%	14%	72%
Frequency of in-person meetings	10%	15%	52%
Resolution of any problems you may have	8%	6%	56%

Table 13: Perception of frequency of contacts by financial advisor (and team)

Client assessment of IBPCG: These measures are less satisfactory (in the aggregate). On the positive side, 42% have brought additional assets to IBPCG. On the negative side, future plans are neutral and respondents do not seem to have noticed an increase in the quality of service. The following table shows a summary of relevant statistical results on this topic:

- Clients have overall demonstrated an interest in maintaining or increasing size of assets invested with IBPCG;
- There exist minor concerns with the level of quality of service provided by IBPCG, specifically in that many clients have not perceived an increase;
- For clients investing new assets, a significant share of the assets transferred to IBPCG came from competitors.

During the next 12 months, you will .... the assets you hold at The Firm?	Increase	Maintain	Partially withdraw	Completely withdraw
	14%	66%	13%	4%
Compared to 12 months ago, would you say that The Firm's current quality of service is...	Much better	Somewhat better	The same	Poorer
	3%	12%	75%	10%
During the past 12 months, have you experienced any problems with The Firm?	NO		YES	
	85%		15%	
Within the past year or so, have you brought additional assets to The Firm?	YES		NO	
	42% (169)		56%	
Would you say that these assets had comprised a ..... proportion of the savings and investments you had held outside of The Firm 169 respondents	Significant Proportion	Moderate Proportion	Small Proportion	
	21%	32%	42%	

Table 14: Client assessment of IBPCG

Assessing reasons to increase assets: Clients generally highly praise the empathy and professional qualities of their FAs and describe them as "trustworthy". However, while the numbers are high, they seem to fall short of 1st of class and suggest that further service improvements are needed to meet that objective. The following table shows a summary of relevant statistical results on this topic:

- Financial advisors are viewed as trustworthy;
- Referrals and advertising have not been very influential on clients' decisions on investing new assets.

Within the past year or so, have you brought additional assets to IBPCG?	YES	NO
	42% (169)	56%

	Extremely Influential 7	Influential 5+6	Neutral 4
Quality of FA service	40%	38%	7%
Quality of FA investment advice	34%	40%	9%
Recommendation received from a friend, family member or colleague	17%	15%	7%
IBPCG product and service offering	21%	43%	7%
IBPCG advertising	4%	11%	9%
Performance of your investments at IBPCG	17%	44%	15%

Table 15 Assessing reasons to increase assets

Clients' expectations of financial advisors: The sets of tables below should be interpreted together. A majority of clients says they would like to be contacted on a regular basis. However, a sizable minority (39%) says they would like to be contacted only when there is a change that affects their account. Still from the answers to the desired frequency of interaction we can interpret that they expect material changes to occur relatively frequently. Our interpretation is that 12/4/2 seems appropriate. The following table shows a summary of relevant statistical results on this topic:

- Many clients claim that they would like to receive more calls than they currently receive;
- 12/4/2 seems generally appropriate according to clients' expectations.

Desired Frequency:

# of calls	11-	12	13+
	64%	16%	15%
# of portfolio reviews	2-	3-4	5+
	59%	25%	16%
# in-person meetings	0	1-2	3+
	18%	49%	23%

Actual Frequency:

# of calls	9-	10-16	17+
	71%	13%	4%
# of portfolio reviews	2-	3-4	5+
	68%	17%	9%
# in-person meetings	0	1-2	3+
	35%	37%	19%

Table 16 Clients' expectations of FA – Part 1

- Most clients are satisfied with the current contact schedule (12/4/2).

Contact preference:

On a regular basis	52%
Only when there is a change that affects your account	39%
I prefer to initiate contact	8%

Assessment of Frequency:

	Too often	Not often enough	Just about right
Contacts are	1%	26%	72%

Table 17 Clients' expectations of FA – Part 2

2.3.2 Summary of Qualitative Findings

- FAs generally support Program Alpha strongly and believe it is a highly beneficial program to IBPCG's business. Financial advisors also profoundly buy into quite the concepts of segmentation and (12/4/2).

- There exist consistent problems related to Program Alpha roll-out from a systems standpoint, which have hampered full program implementation. A standardized contact schedule paradigm, with access levels for financial advisors and client associates is a highly desirable item. Tools to generate customized reports, with deep integration into the TGA system would be highly valued by financial advisors.
- Clients of Program Alpha financial advisors generally feel that the quality of services provided by IBPCG is high, even in comparison with other firms and are satisfied with the services provided by their financial advisor.
- Clients have come to expect this level of quality, which meets but does not greatly exceed their requirements and represent good, but not exceptional, value for their money.
- Clients generally praise highly the empathy and professional qualities of their FA and describe them as "trustworthy". However, while the numbers are high they seem to fall short of first-of-class and suggest that further service improvements are needed to meet that objective.
- The number of contacts with their FA they desire is very close to 12/4/2. The majority of clients wants to have regular contacts, although a large minority wants to be contacted only when there is a need. In general, a large majority thinks that the number of contacts is about right.

Chapter 3

System Dynamics Modeling

The first main goal of this System Dynamics approach to evaluating Program Alpha is to generate program implementation insight that can enhance understanding of the fundamental dynamics behind Program Alpha deployments to date. Secondly, this approach allows for an exploration of organizational, operational and behavioral drivers and hurdles to Program Alpha implementation.

3.1 System Dynamics Overview and Justification

3.1.1 The dynamic nature of an organization

Researchers and managers usually describe an organization of any size or function as an ecosystem of complex interrelationships and interdependencies. While various components of a business are directly and very clearly interconnected, the relationship between disperse elements in an organization is oftentimes difficult to explain or represent in a robust way. These can be financial, economic, operational, organizational, behavioral or even psychological links that all compose a multi-dimensional web of direct and indirect relationships that determine the evolution of a business and its people.

Aside from the fact that certain interrelationships in a system or organization are not generally explicit because they are not direct, it is also the case that time-delay factors can typically make it even less evident to predict that changes in a particular element of the organization may affect others in a significant way. This is especially true in situations where, due to long time delays, secondary effects of a policy can only be perceived many cycles later, possibly after revisions to the original policy have already been implemented. This dynamic may lead to inaccurate perceptions of the true effects of a certain policy and its consequences to the organization in the long run.

Policy resistance is a very common problem faced by managers of all large organizations in the world today. As discussed above, the majority of second- or higher-order relationships between elements of an organization are not apparent and time delays can make it impossible to follow the effects of policy implementation throughout the entire business. Because of these difficulties, it is very often the case that well-intentioned efforts to address pressing problems or business needs lead to delayed, diluted or undesired results, caused by the unforeseen reactions of other individuals or of the organization itself. It is not uncommon to observe scenarios where the best efforts to solve a problem actually make it worse.

3.1.2 System Dynamics Overview

System Dynamics is a method to enhance learning in complex systems. In a similar way as airlines utilize flight simulators to train pilots through various flight conditions and help them learn, System Dynamics can be helpful in generating management flight simulators to help learning about systems complexity, in a way that allows for policies to be tested at a high-level and effects to be analyzed over various time horizons prior to the actual application of a policy.

System Dynamics in itself is a set of conceptual tools for formally representing the relationships among elements of a complex system. It is also a rigorous modeling technique that allows for the construction of detailed computer simulations based on these models and grounded in the theory of nonlinear dynamics and feedback control developed by engineers, mathematicians and physicists.

The central skill of a System Dynamics modeler resides in identifying and formally representing the feedback structures of a system. Careful selection of stocks and flow variables, time delays and non-linearities, along with focused brainstorming to determine the nature of each relationship, can lead to a robust representation of the essential dynamic behavior characteristics of a system.

The majority of System Dynamics practitioners today make use of a graphical representation technique for complex systems known as causal loop diagrams. These diagrams are simple in their nature, and yet capable of easily capturing the feedback structures of a system of many interacting parts. Using this representation, it is easy to see that all dynamics arise from the interaction of just two types of feedback loops: positive (or self-reinforcing) and negative (or balancing/self-correcting) loops.

Figure 3 illustrates a very simple example of interaction between a self-reinforcing and a balancing loop:

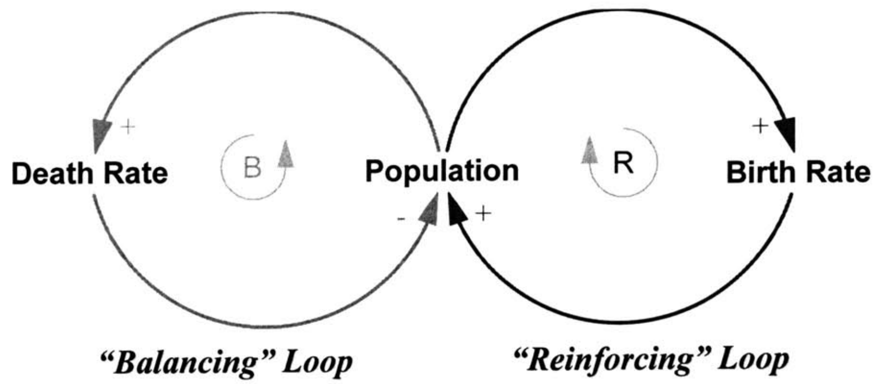


Figure 3: Example of Interaction between a self-reinforcing and balancing loop

- An intuitive representation of population growth says that a higher population level leads to a higher absolute birth rate, which, in turn, contributes to an increase of the population level itself, and so on. This is a self-reinforcing loop that is capable of generating exponential increases in its variables.
- As population level increases, it is also the case that the absolute death rate will go up, as more people reach advanced ages, which, in turn, causes the growth in population level to slow down. This is a balancing loop that causes, over time, a dumping effect in the system and can counteract the effects from a self-reinforcing loop.

Another critically important characteristic and advantage of System Dynamics as a modeling methodology is its flexibility for representing the interactions between quantitative and qualitative elements, specially human factors such as expectations, perceptions, risk, support, knowledge and effort, to mention a few. The modeling exercise in the following sections will make extensive use of this characteristic for representing elements of Alpha.

3.1.3 System Dynamics in the context of Project Alpha

A high-level look at the Alpha implementation process is sufficient for one to suggest that the initiative as a whole lends itself very well to a System Dynamics analysis. The primary reason for such is the existence in the system, defined here as the entire

Private Client organization, of a large number of time-delayed mechanisms and interrelationships between factors of human and operational nature.

Time delays are most often present in business policy implementation scenarios where human processes are affected, directly or indirectly, by the changes being introduced. Humans whose work processes are undergoing changes need time to learn new tools, new approaches to doing business, or even an optimal way to interact with new colleagues in a department given the different scenario being introduced. People also need time to phase out of their current habits and attitudes before they are fully accommodated in a new model. All of these activities simply take time.

In the context of Program Alpha implementation, several time-delayed mechanisms have been observed. Some examples include:

- **Knowledge acquisition**: looking at Program Alpha as a fundamentally new philosophy to serving clients' needs, the implementation process entails a relatively complex knowledge installation process. From initial kick-off training to several other levels of knowledge transferring and recycling, the time it takes for a financial advisor to be completely accustomed to Alpha can easily approach 2 years.
- **Client migration**: the process of transferring clients away from the auspices of a financial advisor and either into another financial advisor or a different department within the Private Client business can take some time. Firstly, there may be psychological ties that prevent the personal relationships from ceasing easily. The client may also require intense hand-holding throughout the process and it may be quite a few months until the financial advisor can completely let go

and still be relatively secure that the client will not withdraw from the firm a significant portion of invested assets.

- **Acceptance**: a financial advisor cannot be expected to instantaneously accept and fully adopt a completely new service paradigm that modifies the fundamental basis on which he/she works on a daily basis. This acceptance process is lengthy and has dependencies on observation of results and interactions with colleagues undergoing the same process. Once again, this is a time-consuming process.
- **Technology adaptation and new processes**: one of the principal elements of Program Alpha is the new segmentation and client management system introduced with the program. Despite the fact that the system initially introduced will still undergo an improvement and standardization process, it is fact that an effective Alpha financial advisory team (FA + CA) will need to make use of IT systems intensely in order to reach a high level of performance and efficiency. Training and ramp-up time for those new systems can be a particularly lengthy project, specially for certain financial advisory teams currently not relying much on IT.

Time delays aside, most of the mechanisms involved in the implementation of Program Alpha at IBPCG include factors of various natures interacting in real-time to produce all the effects associated with the program, whether desirable or non-desirable. Factors accounting for various modes of system behavior may come from organizational, operational or psychological sides.

These multi-factor/multi-disciplinary mechanisms will be explored in detail in dynamic hypotheses presented in the following sections, but overall it suffices to say they represent a complex interaction that is not easily and singly accounted for by statistical, financial or optimization models.

3.1.4 Dynamic insight

The value of System Dynamics in evaluative stages of Program Alpha consists essentially of projecting the potential magnitude of impact that various factors may have on the system over time, as the program continues to be implemented across the country.

The System Dynamics micro-models presented in the following sections for the most part explore the effects that operational levers can have over the financial advisor's team, in terms of perceptions, expectation forming and even performance and effectiveness.

While the models and dynamic hypotheses explored in the next section are far from being thorough to the point of simulating reality, they do contain elements that resemble the general dynamic behavior observed not only in the context of Project Alpha, but also in a variety of similar scenarios explored by experts from the field during the last three decades. The level of insight expected from these models is:

- **Delayed effects**: assess the potential order of magnitude of policy effects only perceived after significant time delays.
- **Policy interaction**: assess the consequences of overlapping various (possibly semi-contradictive) implementation policies or guidelines.
- **Operational gaps**: evidence and amplify the effects of operational gaps in the system by simulating extreme scenarios.
- **Attitudinal impact**: assess the level of impact of current operational gaps on future attitude and behavior (e.g. accumulating frustration).

Despite the importance of the items above, perhaps the principal value generated by the exercise of building a System Dynamics macro-model such as the one introduced in the next section, however, comes not exactly from the model or the simulations themselves, but from the building process.

The model building process is one that relies heavily on participation of individuals who understand the system deeply at different levels and from different points of view (operational, strategic, managerial). Not only does the process allow for these individuals to lay out their thinking in great detail, it accomplishes two very important tasks.

Firstly, it forces all minds around the table into a structured thinking process centered around a fundamental understanding of the system rather than on the need to make a decision under pressure. Secondly, it forces these individuals into expressing their mental models and explicitly opening them to colleagues who may be able to point out a number of the inherent flaws.

In summary, the System Dynamics modeling process creates a healthy discussion forum that stimulates critical thinking and constructive criticism that ultimately leads to a better collective understanding of the dynamic complexity of a system, even before any models are finalized and simulated. In order for that process to be optimal, participation from a high number of individuals of different specialties/focus areas is not only important but also necessary.

3.2 The Program Alpha Macro-model

The first step in the System Dynamics modeling process consists of constructing a high-level picture of the system under consideration. The following diagram illustrates the approach selected for this project. We explore organizational, operational and behavioral drivers and hurdles to analyze the dynamics of Program Alpha implementation.

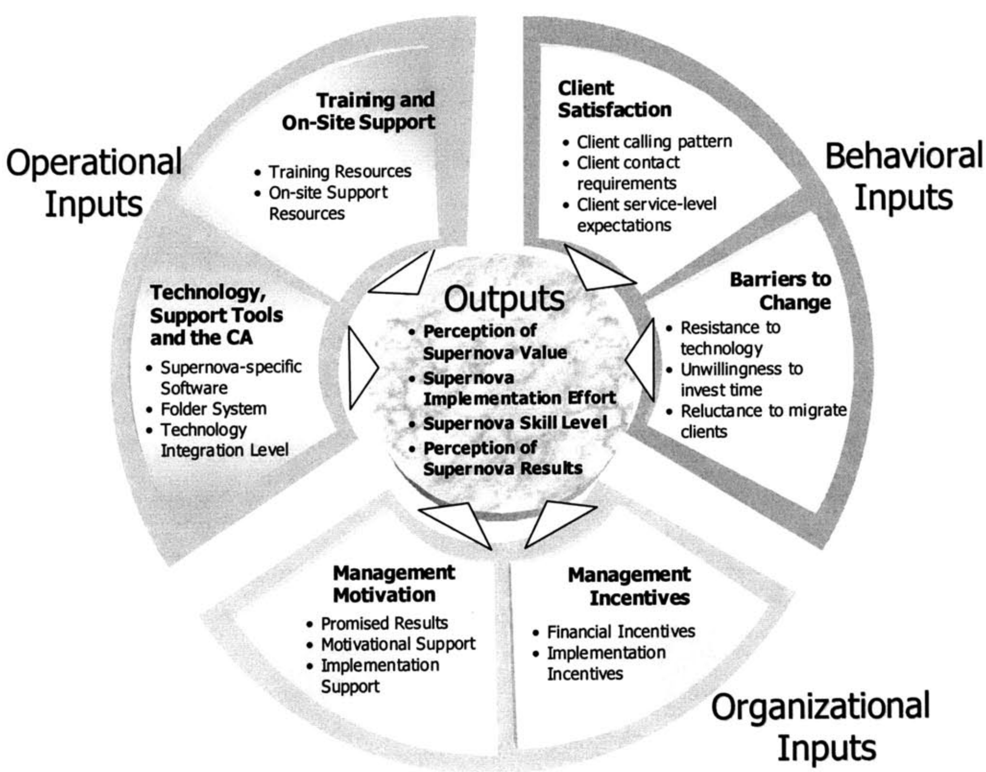


Figure 4: Organizational, Operational and Behavioral Drivers

3.3 Program Alpha Micro-models and Dynamic Hypotheses

In this section, we will separately analyze various components of the macro-model introduced in the previous section. Each micro-model is associated with a dynamic hypothesis, which is an assumption as to how the system would likely behave under various conditions of the input parameters.

A typical approach to System Dynamics modeling would call for a series of management brainstorming sessions to create initial dynamic hypotheses such as the ones presented in this section. The process that would naturally follow would involve in-depth data gathering and interviewing of numerous individuals involved with the "system" under discussion. The subsequent step would be a systematic modeling and simulation effort that not only validates and adjusts the dynamic hypotheses presented, but connects them in a coherent fashion. After various iterative review steps, the end result is a functional System Dynamics model that can be used as a tool in various occasions, including training, decision support, forecasting, or simply as a jointly produced representation of an organization and its dynamic behavior, for management reference.

This section presents preliminary results of the very first step of the System Dynamics modeling approach outlined above. Based on data from management interviews, focus groups and the telephone interviews (FAs and clients), many micro models and corresponding dynamics hypotheses were generated and three of them are presented here.

3.3.1 Micro-model: Management incentives and motivational support

From very early discussions held with IBPCG's management during the early phases of this project, it appeared that one of the central elements in generating interest and promoting successful deployments of Program Alpha was, in fact, the level of managerial support at various levels to the program.

Comparing observations made at the Boston and Kansas City complexes, it became quite clear that the level of management commitment to Program Alpha in either case differed significantly. While at the Kansas City complex, Program Alpha seemed to occupy one of the leading spots in the management's agenda, in the Boston complex it appeared that managers were committed to the program, but not as directly involved in pitching and pushing it as their Midwest colleagues. It was simultaneously observed that financial advisors in the Kansas City complex were substantially more knowledgeable about and interested in the program, as well as generally more advanced in its implementation.

Managerial support of Program Alpha involves allocating time and effort to understand, show support for, create incentives and clear obstacles to the program. Management support and incentive generally raise the interest level of financial advisors and make the program more attractive, as it demonstrated the potential for contributing to IBPCG as a whole and to one's own career.

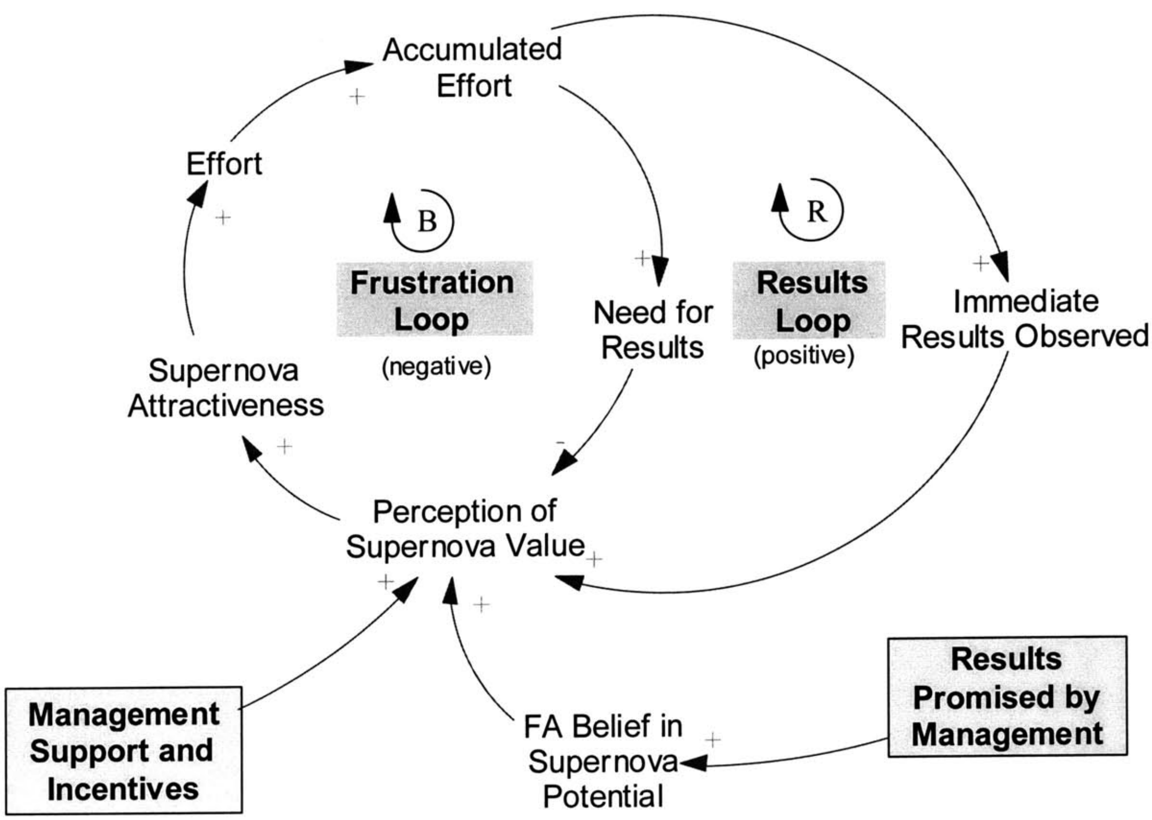


Figure 5: Management Incentives and Motivational Support

As

Figure 5 above shows, as financial advisors start to perceive value in Project Alpha, they acquire an increasing sense of attractiveness by the potential of becoming an official 'adopter'. As this perception builds up among financial advisors, it starts to get converted into actual implementation effort, which builds up over time. As a result of continued effort and dedication to the program, some positive results are eventually perceived and those convert into an even greater perception of value in Project Alpha, closing the reinforcing loop ("Results loop").

At the same time, the more effort financial advisors accumulate in implementing Project Alpha, the higher their expectations become with regards to a psychological need to observe positive results. As expectations build up further and further, they come to a point where short-term results are not satisfactory, which leads to a drop in the perceived overall value of the program, which reduces the attractiveness level and so on. This rationale generates a balancing loop ("Frustration loop") shown also in Fig. 18.

The main reference modes for this micro-model are shown in figure 19. A reference mode is essentially an assumption or actual observation of a variable (very specific or very broad) that serves as a basis for a dynamic hypothesis, as well as a behavioral "check" for the system as modeled. The charts below are not particularly crafted from hard observations, but instead are a general interpretation of possible scenarios. They are, however, influenced by the comparisons drawn between the Kansas City complex and the Boston complex.

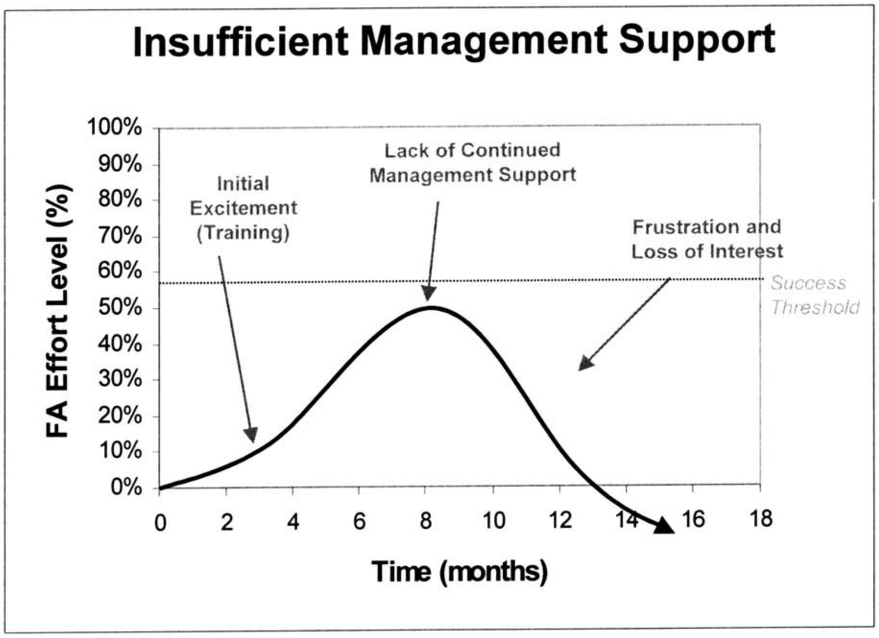


Figure 6: System Behavior: Insufficient Management Support

In the insufficient management support scenario, initial financial advisor excitement is generated by early training exercises and overall stimulation provided my management, mostly a natural process due to the excitement normally associated with the "novelty". At some point during the relatively early phases of Program Alpha implementation, a cease of continued and explicit management support and stimulation may cause the "Frustration" loop to kick in strongly and bring the system down quickly. Frustration rapidly leads to discontinued implementation effort and may even generate an anti-program mentality among financial advisors, represented in the graph by the asymptote negatively crossing the zero-effort level (shown in figure 19).

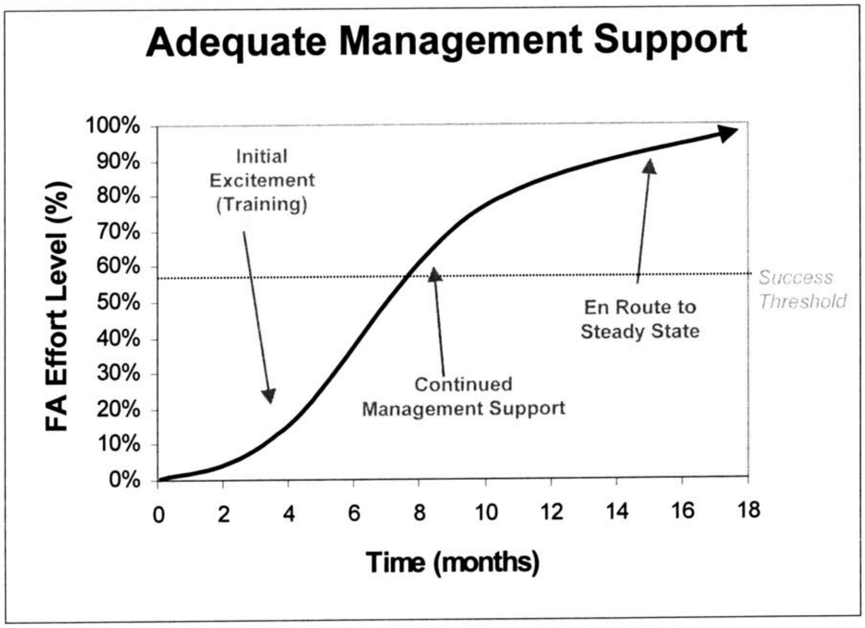


Figure 7: System Behavior: Adequate Management Support

Under the scenario of adequate management support (fig. 20), the same initial excitement level leads to a rapid increase in support and effort employed for implementation of Project Alpha. Throughout the program, management continually injects incentives and support into the system by constantly checking in with financial advisors and closely observing and reviewing their activities and results. By constantly feeding the reinforcing loop past the "success threshold", this management support structure prevents the "balancing loop" from kicking in early and directs the system to a steady state mode where it is mostly self-sustaining.

3.3.2 Micro-model: Training and on-site support

The dynamic hypothesis of this sub section claims that training and on-site support are separate initiatives from the point of view of how they influence the financial advisor's adoption curve and effort level throughout the implementation of Project Alpha.

Based primarily on observations from the focus group discussions and the financial advisory opinions expressed through the telephone questionnaires, it was determined that perhaps the specific role and value added of training and explicit support activities was not precisely delineated by the program designers and implementers. Along the same lines, it also seemed clear that the timing and content of training and "refresh" sections had possibly not been as carefully thought and planned such as to optimize their value to financial advisors.

As the diagram below shows, initial implementation effort by financial advisors is triggered by training activities that raise the awareness level and general Project Alpha-specific knowledge. Through a mechanism very similar to the one presented in the previous section, awareness is converted into implementation effort, generating results and an immediate perception of value, which in turn raises the attractiveness of the program to each financial advisor and continues to drive further implementation efforts. This rationale generates a reinforcing loop shown as

Figure 8.

At the same time, we assume the existence of a "stock" of problems or implementation hurdles that are "discovered" over time. The discovery of such hurdles is directly proportional to the level of implementation effort being employed by financial advisors. As new implementation hurdles are discovered, more on-site support is needed to address those issues to allow financial advisors to move on with program roll-out. The more on-site support is needed, the less adequate any given level of support will seem to the financial advisor. The perception of inadequate support will lead, in turn and relatively speaking, to a decrease in the Project Alpha-specific skill level, which drives down the level of effort being dedicated by the financial advisor. This rationale generates a balancing loop shown above.

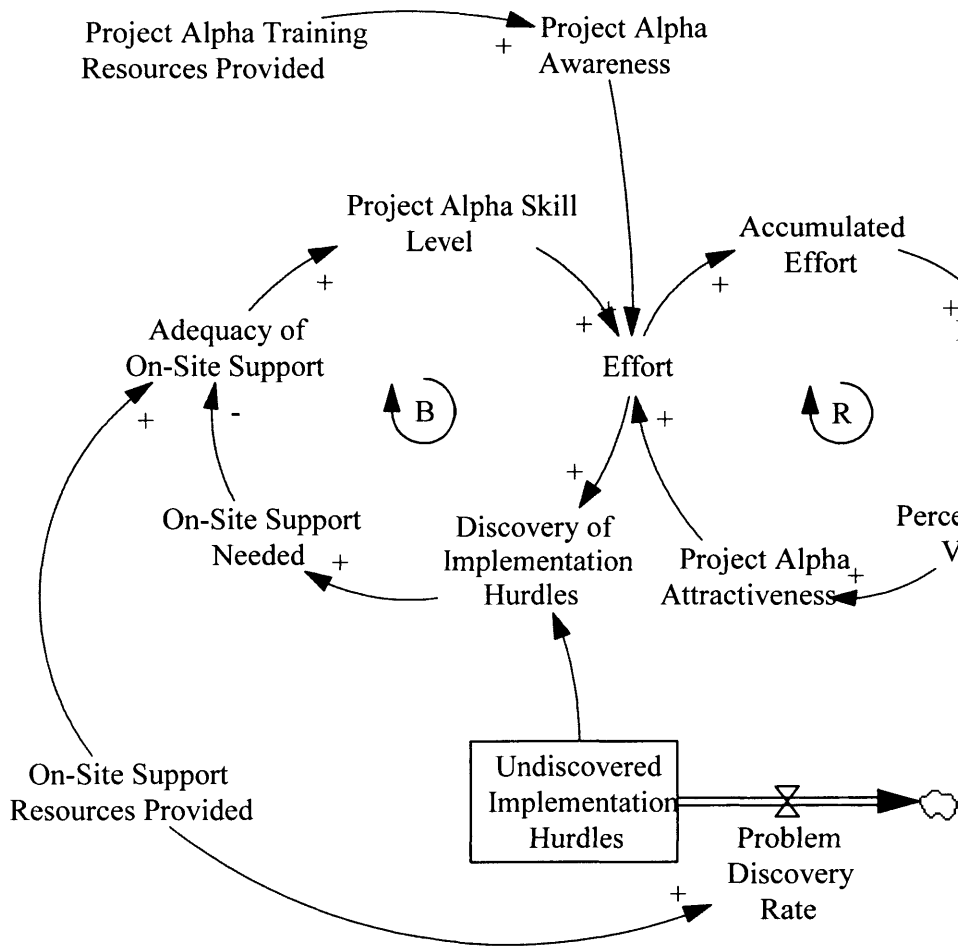


Figure 8: Training and On-Site Support

3.3.3 Micro-model: Technology, support tools and the role of the CA

The dynamic hypothesis of this section claims that properly developed and well integrated technology and support tools are necessary requirements for a successful roll-out of Project Alpha. At the same time, the impact of proper technology and support tools cannot be fully realized without strong and active participation from client associates (CAs).

Observations from focus group discussions, management interviews and the telephone questionnaires all pointed unanimously to technology as the largest handicap of the current implementations of Project Alpha. Issues around the sheer functionality of the segmentation and client management system were brought up, mainly pointing to the fact that these new tools were not customizable to the needs of a financial advisor or to particular client sets. At the same time, all financial advisors were strongly positioned in favor of a much higher level of integration between the new systems and some of the existing software, including the standard financial advisor platform (three-letter acronym) and a standardized scheduling system.

The diagram below shows a micro-model that differs from the previous ones in its structure. Rather than identifying high-level variables and their intangible relationships, very specific and deterministic links between tangible elements were created. The essential mechanism of this micro-model revolves around the role of the client associate (CA) as the individual who serves, under an ideal Program Alpha scenario, as:

- **Filter**: screen calls and client issues in attempt to resolve them without having to access the financial advisor directly. This allows the financial advisor to focus on scheduled activities and follow the Program Alpha specifications more attentively.
- **Organizer**: have direct access to and be able to operate the IT systems that support the financial advisor. This allows the financial advisor to outsource secretarial level scheduling and schedule changing tasks to the client associate.
- **Enforcer**: have direct access to scheduling system. This puts the client associate in a position to ensure that financial advisors attend to every client commitment in a timely fashion.

There are three key variables in the diagram shown in the next page. The first variable that influences the system quite profoundly is the client associate's level of Program Alpha skill, which comes primarily from direct training, as well as coaching from the financial advisor.

Another important variable that affects the essential mode of operation of this model is the share of incoming calls actually handled by the client associate. This number is heavily influenced directly by the client associate's Program Alpha skill level and helps determine the actual rate of incoming calls passed to the financial advisor, which is a key bottleneck to Project Alpha.

The final and probably most important variable in the context of this micro-model is the main output number: proportion of scheduled phone minutes to incoming phone minutes. This variable indicates what proportion of time financial advisors spend with clients in systematically planned calls scheduled ahead of time versus calls initiated by clients directly, due to specific concerns or account-related questions. A high concentration of scheduled calls not only indicates that clients are properly "trained" to wait until the next call to ask questions, but also that client associates are playing an efficient role in keeping clients with "easy questions" away from the financial advisor if the topics are not critical, either by addressing them directly or convincing the client to postpone it until the next call.

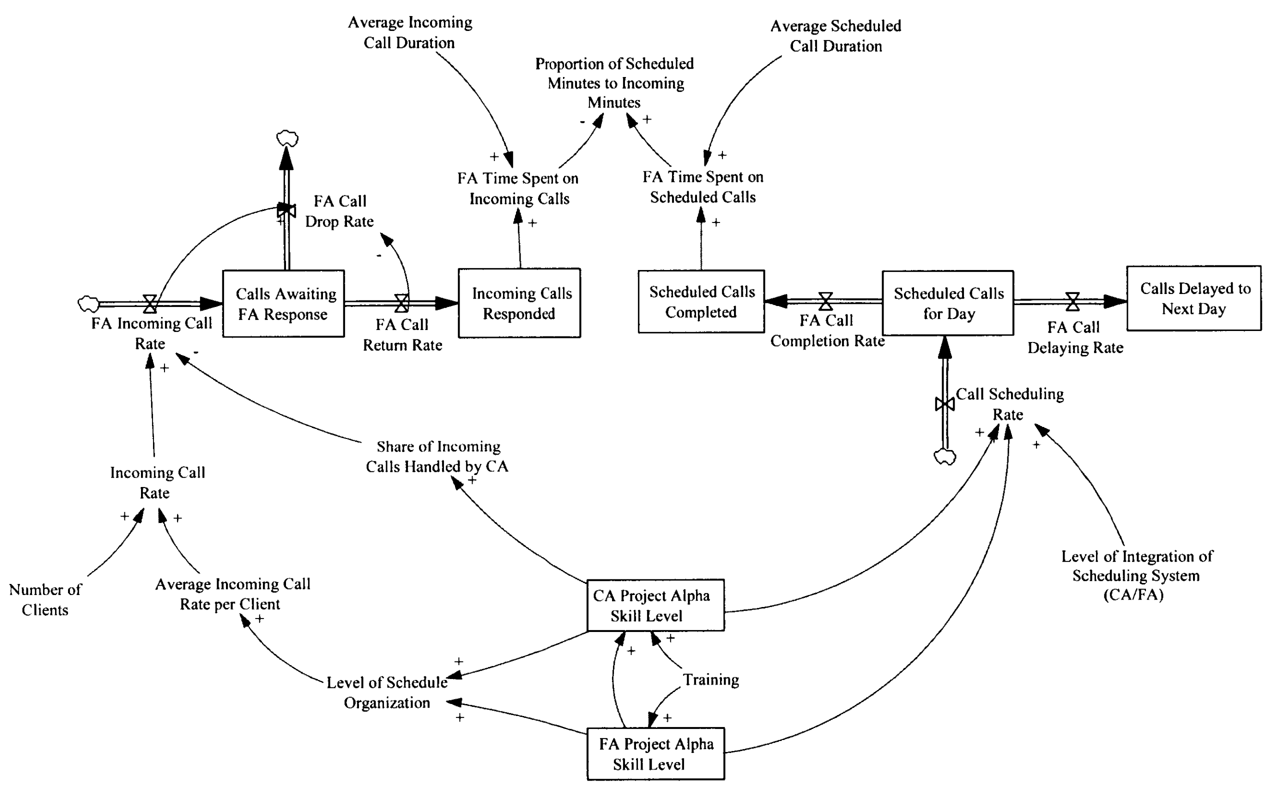


Figure 9: Technology, Support Tools and the Role of the CA

3.4 Summary of findings

With respect to management's influence and support, district and branch managers should be ready to play a very important role throughout the implementation of Project Alpha, especially in the early phases of discontinuity and uncertainty. Motivational support and explicit incentives may be necessary requirements for a successful kick-off of the program in districts, as well as successful development through steady state.

On the training and on-site support category, Program Alpha kick-off training sessions should be regarded as just the beginning of the educational effort required for a successful implementation. On-site support by individuals familiar with Program Alpha practice and tools is necessary for continued learning by FAs and CAs. "Refresher" training courses are also important on a regular basis even beyond steady state, but are not substitutes for an on-site support staff.

On the technology and support tools topic, CAs play a key role during Program Alpha implementation and execution: Filters, organizers, enforcers. Most FAs with 200+ accounts can only feasibly achieve the 12/4/2 service level for all passenger clients if they are able to eliminate a significant amount of time performing non-core activities, which should be fulfilled by the CA. Strong CA involvement in Program Alpha implementation and execution is ultimately a requirement for a successful transition into the "Client Acquisition" phase.

Chapter 4

Data Mining Framework

This chapter lays out a preliminary and simplified approach to a methodology for creating a classification algorithm that allows FAs to partition their book of clients (or households, as they are more frequently referred to) into three separate groups:

- clients that the financial advisor will keep within his or her book;
- clients that will be transferred to another financial advisor not enrolled in Program Alpha;
- clients that will be transferred to IBPCG's non-dedicated call center-based advisory division.

Program Alpha specifications instructed FAs to segment and transfer clients primarily based on the dollar amount of assets invested with IBPCG through that financial advisor. Clients with assets under a certain amount were regarded as undesirable, partly because some were clearly not profitable to IBPCG from a fees perspective, and partly because some were potentially not profitable to IBPCG when accounting for the advisory personnel time they consumed vis-à-vis the cost of those individuals to IBPCG.

Since Program Alpha's first deployment, over 100 FAs throughout IBPCG have adopted and begun to implement the program's methodology for client segmentation and service. Among these early-adopter FAs, about a third is comprised of individuals who have really dedicated time and thought not only into deploying the originally designed guidelines, but principally into adapting them to their reality and the specific characteristics of their clients.

This chapter focuses on statistically extracting a "formula" for client segmentation out of the activities and choices made by this small group of "strong implementers" or "benchmark FAs". Specifically, a supervised statistical learning framework is proposed to effectively generate and train a model that encapsulates the segmentation criteria used by the benchmark individuals. This model is then used to verify (through scoring) whether the "non-benchmark FAs", i.e. those individuals who have not necessarily invested as much time and effort into following Program Alpha's specific guidelines, have used similar criteria to segment their clients and transfer a portion of them outside of their books.

The proposed approach will help determine whether the "official" segmentation rules are the most effective ones and whether alternative segmentation rules may be even more effective. In addition, it will provide a benchmark as to whether FAs are being truly effective in segmenting their client base.

In essence, the proposed approach ultimately aims to generate an algorithm that FAs who are starting to implement Program Alpha can use to determine how to segment their client base and specifically which clients to transfer out of his or her book. This chapter lays out the statistical framework behind such an algorithm.

It is important to note throughout this analysis that the methods described may have statistical significance drawbacks due to the fact that the data sets currently available cover a relatively small number of FAs and clients. The data sets used are also sparse, as many of the data points had missing values for several important variables and had to be selectively discarded.

4.1 Methodology

The method used in this chapter consists of supervised learning of client segmentation criteria, based on financial advisor 'best-practice' behavior. Under this scenario, the FAs who have clearly demonstrated to be strong implementers of Program Alpha are assumed to be the benchmark classification model, or, in other words, practitioners of the most effective 'formula' for selecting clients to be transferred out of their books. The group of strong implementers was primarily identified via a special email survey that asked FAs a number of questions related to their degree of adoption of Program Alpha.

This method will determine what criteria those FAs who are strong implementers of Program Alpha effectively used. It will also determine whether FAs who are weak implementers of Program Alpha followed similar segmentation criteria as the strong implementers.

Additionally, this method will display specific misclassification evidence in segmentation between benchmark and non-benchmark FAs, showing where segmentation decisions could have differed if criteria adopted by the strong implementers were used across the board.

A slightly unrelated analysis task was also performed in this chapter. Since segmentation of clients was being analyzed from a point of view of clients kept within a certain financial advisor's book or transferred out, it would also be valuable to deliver some insight on client accounts that were closed by clients themselves and what factors may have influenced such decision in the context of *Program Alpha* implementation. This process was carried out through a simplified unsupervised classification and regression model.

4.1.1 Data Set

The data set available for this chapter corresponds to client information divided into two main periods: (a) client behavior during approximately one year prior to the implementation of Program Alpha (PRE data set) and (b) client behavior during approximately one year (POST data set), as shown below:

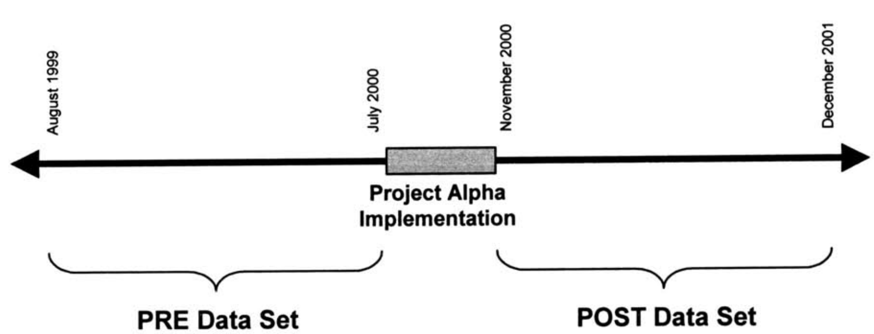


Figure 10: PRE and POST data sets

Clients of 140 FAs are included in the sample. 24,589 total clients are included in the PRE data set and 20,214 total clients are included in the POST data set, as detailed below:

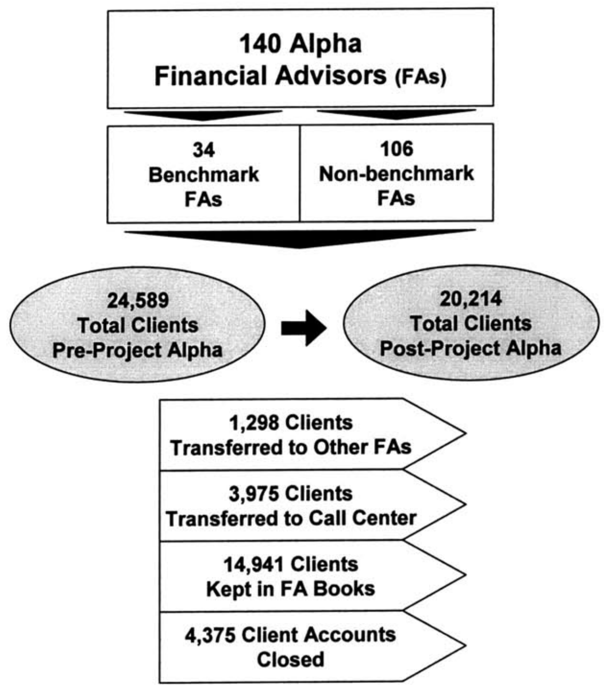


Figure 11: Total clients in PRE and POST data sets

In the diagram above, a distinction was drawn between two groups of FAs. FAs referred to as "benchmark FAs" are those self-assigned as strong implementers of Program Alpha. The remainder FAs are classified as "non-benchmark FAs".

This chapter's approach (supervised learning of segmentation criteria) will only use the PRE data set and attempt to draw conclusions upon what client characteristics the benchmark FAs looked for in clients prior to Program Alpha implementation that led them to believe those clients were the correct ones to be transferred.

An analysis and approach that are outside of the scope of this chapter, but that could be performed on this data set would be an unsupervised learning of client responses to the implementation of Program Alpha. Such a task would observe the change in variable values between the PRE data set and the POST data set. Through clustering analysis, that difference would effectively be used to determine how individual clients who have been transferred to another financial advisor or to the call center-based advisory division have reacted, compared to clients who have been kept by the same financial advisor. Clustering analysis would be applicable in this case, as it would help identify groups of "types" of clients with similar characteristics and "reaction" to Program Alpha.

The PRE data set consists of the following variables, measured for the period August 1999 and July 2000:

Variable Name	Variable Type	Variable Description
Group	Nominal	Transfer status (staying with *Program Alpha* FA, transferred to non-*Program Alpha* FA, transferred to call center).
HH_ID	Nominal	Account identification number.
FA_ID	Nominal	Financial advisor (or advisory team) identification number.
BenchM	Binary	Financial advisor belongs to benchmark/strong implementer set.
		Financial Variables
PreAssets	Interval	Total asset dollar value.
PreDebt	Interval	Percentage of assets invested in debt.
PreEquity	Interval	Percentage of assets invested in equity.
PreFee	Interval	Total dollar fees generated.
PreFeebsd	Interval	Total asset dollar value invested in fee-based products.
PreMargin	Interval	Dollars of margin interest paid.
PreMFunds	Interval	Percentage of assets invested in mutual funds.
PreCash	Interval	Percentage of assets in cash.
PrePCs	Interval	Production credits generated.
PreTrades	Interval	Number of trades executed.
PreNAccts	Ordinal	Number of accounts held by that client.
		Behavioral Variables
CAServPre	Ordinal	Quality level of service provided by financial advisor's assistant.
ContPre	Ordinal	Frequency of contact by financial advisor.
FAServPre	Ordinal	Quality level of service provided by financial advisor.
MLServPre	Ordinal	Quality level of service provided by IBPCG.
ProbPre	Binary	Client indicated they had problems.
ServValPre	Ordinal	Overall rating of financial advisor's value for fees charged.

Note that the variables displayed in the tables above have been selected as the most relevant of a large set of client-related variables.

It is also important to note throughout this analysis that the methods described above may have statistical significance drawbacks due to the fact that the data sets currently available cover a relatively small number of FAs and clients. The data sets used are also sparse, as many of the data points had missing values for several important variables and had to be selectively discarded.

4.1.2 Methodology for Supervised Learning of Segmentation Criteria

The process described in this section consists of a slightly modified supervised learning and scoring procedure.

- A **training set** is created as a benchmark for the classification process (a sub-group containing half of the clients of the 34 benchmark FAs, randomly selected);
- A **test set** is used to effectively validate the trained model (a sub-group containing the remaining half of the clients of the 34 benchmark FAs);
- A **scoring set** is then used to perform classification of new data (a group containing all clients of the 106 non-benchmark FAs).

The 'scoring set' effectively consists of clients who have already been classified by FAs and either kept in the financial advisor's book or transferred out. The added step in this classification procedure consists of evaluating the choices made by those FAs based on the trained model. In other words, this approach will verify whether non-benchmark FAs tended to follow similar procedures for client segmentation as 34 the benchmark FAs.

The classification techniques used for this portion of the analysis were **classification trees** and **logistic regression**. The sole dependent variable for this supervised learning model is `Group`, which qualifies each client account as a *Program Alpha* account, an account transferred to a non-*Program Alpha* financial advisor, or an account transferred to the call center. All other financial and behavioral client variables are the independent variables used as inputs to the model.

The training process for the supervised learning model can be summarized as a process for determining the specific criteria used by FAs to segment and transfer clients outside of their books. The objective is to generate a model that explains which variables influenced a segmentation decision positively or negatively and with what magnitude.

4.2 Analysis

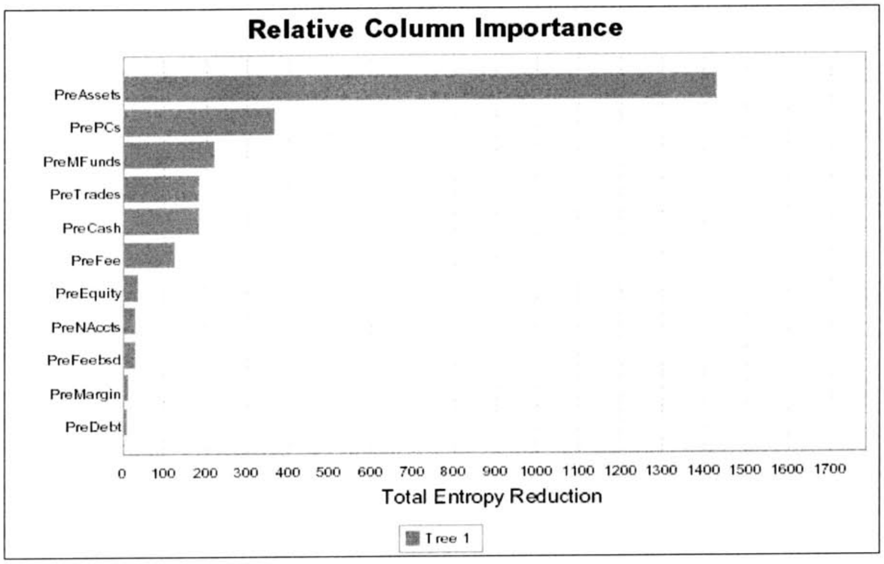
4.2.1 Supervised Learning of Segmentation Criteria

Two different supervised learning models were created for this analysis. The first model includes financial data variables, based on a total of 6,841 client data points divided between training and test sets. The second model includes both financial and behavioral variables, based on 756 client data points, also divided between training and test sets.

Conceptually speaking, while the second model is the ideal approach from a methodology perspective, its results and prediction capability may not be statistically significant due to the small size of the underlying data set. The first model, while excluding potentially valuable and relevant variables, is based on a much higher number of observations and would have a conceptually better prediction capability.

4.2.1.1 Supervised Learning using Financial Variables

Tables 3.1.1a, 3.1.1b and 3.1.1c display training results from the first supervised training model using classification tree and logistic regression techniques, based solely on client financial variables, as indicated above.



Classification Tree Analysis

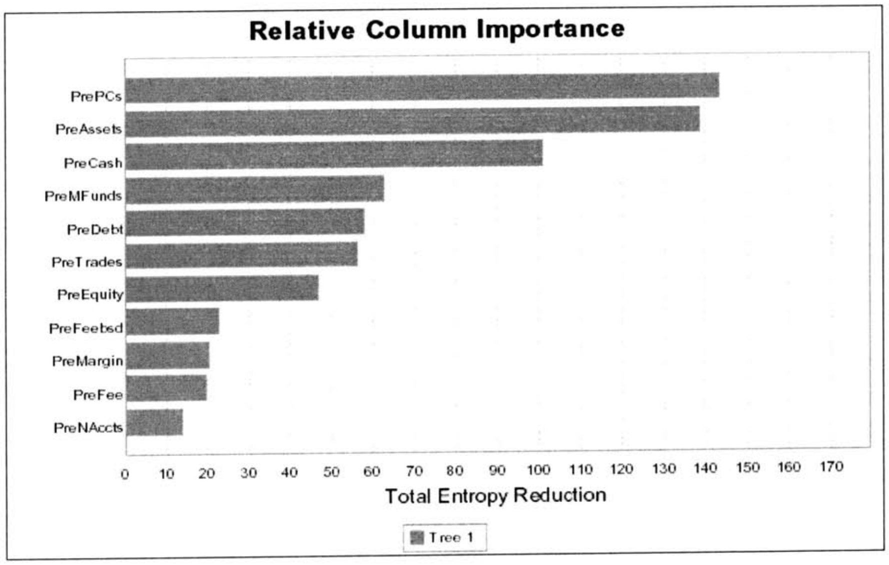
Coefficient Estimates			
Variable	**Estimate**	**Std.Err.**	**t-Statistic**
PreAssets	-0.01	5.2E-7	-13.80
PreDebt	0.09	0.15	0.56
PreEquity	-0.02	0.10	-0.17
PreFee	-0.01	2.8E-4	-4.88
PreFeebsd	2.4E-6	1.0E-6	2.38
PreMargin	2.6E-3	3.6E-4	7.01
PreMFunds	0.25	0.07	5.39
PreCash	-0.21	0.09	-2.31
PrePCs	-0.01	6.6E-5	-5.35
PreTrades	-0.07	0.02	-3.49
PreNAccts	-0.04	0.04	-1.18

Coefficient Estimates (Most Significant Variables)			
Variable	**Estimate**	**Std.Err.**	**t-Statistic**
PreAssets	-0.00	4.6E-7	-16.72
PreMFunds	0.20	0.06	4.22
PrePCs	-0.00	6.6E-5	-7.10
PreTrades	-0.08	0.02	-4.06

Correlated Coefficients	
Coefficients	**Correlation**
PreMFunds and PreTrades	-0.54

Logistic Regression Analysis

Table 18: Training using financial variables (FAC_transfer group)



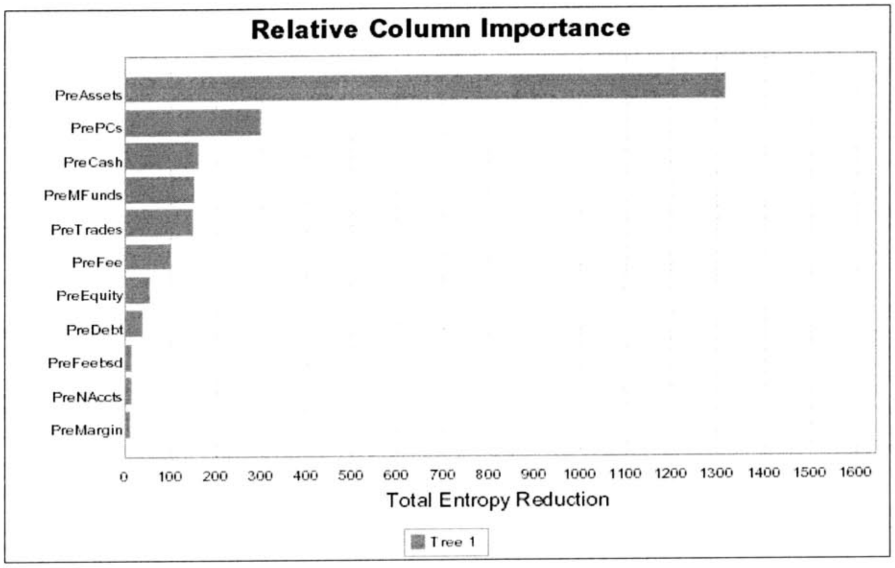
Classification Tree Analysis

Coefficient Estimates			
Variable	**Estimate**	**Std.Err.**	**t-Statistic**
PreAssets	-0.01	2.4E-7	-2.57
PreDebt	-1.82	0.20	-9.07
PreEquity	-2.19	0.15	-14.71
PreFee	7.8E-5	1.3E-4	0.60
PreFeebsd	-0.01	7.5E-7	-1.54
PreMargin	1.9E-4	3.4E-4	0.55
PreMFunds	2.82	0.13	3.27
PreCash	-2.02	0.14	-14.73
PrePCs	-0.01	3.9E-5	-1.48
PreTrades	-0.07	0.02	-3.18
PreNAccts	-0.15	0.05	-3.38

Coefficient Estimates (Most Significant Variables)			
Variable	**Estimate**	**Std.Err.**	**t-Statistic**
PreAssets	1.2E-6	2.1E-7	-5.35
PreDebt	1.95	0.20	10.02
PreEquity	2.45	0.14	17.85
PreMFunds	2.90	0.10	29.63
PreCash	2.18	0.13	17.28

Logistic Regression Analysis

Table 19: Training using financial variables (FA_transfer group)



Classification Tree Analysis

Coefficient Estimates			
Variable	**Estimate**	**Std.Err.**	**t-Statistic**
PreAssets	3.6E-6	3.0E-7	12.06
PreDebt	-0.14	0.14	-1.02
PreEquity	0.03	0.09	0.31
PreFee	6.1E-4	1.6E-4	3.89
PreFeebsd	-0.01	6.8E-7	-0.18
PreMargin	-0.01	2.7E-4	-5.21
PreMFunds	-0.22	0.07	-3.37
PreCash	-0.05	0.09	-0.64
PrePCs	2.0E-4	4.2E-5	4.80
PreTrades	0.06	0.02	3.72
PreNAccts	0.05	0.03	1.69

Coefficient Estimates (Most Significant Variables)			
Variable	**Estimate**	**Std.Err.**	**t-Statistic**
PreAssets	3.7E-6	2.7E-7	13.72
PreFee	6.6E-4	1.5E-4	4.34
PreMargin	-0.00	2.7E-4	-5.16
PreMFunds	-0.18	0.06	-3.00
PrePCs	2.1E-4	3.9E-5	5.52
PreTrades	0.08	0.02	4.85

Coefficients	Correlation
PreMFunds and PreTrades	-0.55

Logistic Regression Analysis

Table 20: Training using financial variables (no_transfer group)

Upon analyzing Tables 18, 19 and 20, a few conclusions can be drawn:

- As expected from the basic guidelines of *Program Alpha*, most FAs in the benchmark group base themselves on each client's `asset size` and `production credits` to determine whether to keep them in their books or transfer them out. Indeed, large negative coefficients in the `FA_transfer` and `FAC_transfer` groups indicate that clients with small accounts generating little revenue to IBPCG are the first to be transferred out of a financial advisor's book during implementation of the program. Large positive coefficients in the `no_transfer` group indicate clients with larger accounts generating more revenue to IBPCG are not transferred out.
- A large percentage of assets invested in mutual funds may have been a strong reason for transferring clients out, mostly to the call center. Given that the correlation between `PreMFunds` and `PreAssets` or `PrePCs` is not very strong, it is possible to conclude that a number of clients may have indeed been transferred out for that reason.
- Clients with high trading activity seem to have been generally kept by the financial advisor, although with a lesser importance as a criterion than the other variables mentioned. To add a note to this and the previous observation, there is a significant negative correlation between `PreMFunds` and `PreTrades`, which is not surprising, given that clients who invest in mutual funds tend to look for stability and trade in very low to zero volumes.
- Most benchmark FAs did not seem to pay special attention to a client's level of annuitized invested assets as a criterion for segmenting their books. Given that one of Program Alpha's design fundamentals is centered around moving clients' assets into an annuitized model, this may be a relevant finding that states that FAs are "starting from scratch" as far as annuitizing clients' assets, and prefer to select clients with high future earning potential than clients who are already partly moved into an annuitized model.

Input Node - Classification Tree (1)					
		Predicted			
		SN	*FA*	*FAC*	*Totals*
Observed	*SN*	4191	7	472	4670
	FA	350	14	71	435
	FAC	795	4	937	1736
	Totals	5336	25	1480	6841

	Observed			
	SN	*FA*	*FAC*	*Overall*
% Agree	*89.7%*	*03.2%*	*54.0%*	*75.2%*

Table 21: Training using financial variables

Table 21 shows the training performance on the test data set of the first model generated by the classification tree method. Table 3.1.1e below shows the predicting performance of this model using the scoring data set of non-benchmark FAs. The scoring set contains 17,748 data points, which correspond to clients of weaker implementers of Program Alpha.

Input Node - Predict: Classification Tree (3)					
		Predicted			
		SN	*FA*	*FAC*	*Totals*
Observed	*SN*	9784	46	1874	11704
	FA	694	9	277	980
	FAC	2442	29	2593	5064
	Totals	12920	84	4744	17748

	Observed			
	SN	*FA*	*FAC*	*Overall*
% Agree	*83.6%*	*00.9%*	*51.2%*	*69.8%*

Table 22: Scoring of non-benchmark clients using financial variables

By analyzing Table 22, one can observe the following points:

- Non-benchmark FAs seem, for the most part, to agree with benchmark FAs on their segmentation criteria, with some potential differences in how they select clients to be transferred to the call center (FAC).
- Non-benchmark FAs seem to have transferred more clients to FAC than the benchmark FAs would have done in their places.
- Our model for explaining selection criteria for migration of clients to other FAs seems quite poor. The models for selecting which clients to keep or transfer to FAC is much more robust, relatively speaking and on an absolute basis.

4.2.1.2 Supervised Learning using Financial and Behavioral Variables

Tables 3.1.2a, 3.1.2b and 3.1.2c display training results from the second supervised training model using the logistic regression technique, based on client financial and behavioral variables. No classification tree algorithms were used in this sub-section because those did not converge properly.

Coefficient Estimates			
Variable	**Estimate**	**Std.Err.**	**t-Statistic**
PreAssets	-0.01	4.5E-6	-2.58
PreDebt	-3.78	1.95	-0.93
PreEquity	-2.72	1.53	-0.78
PreFee	1.2E-3	1.3E-3	0.91
PreFeebsd	-0.00	1.3E-5	-1.14
PreMargin	2.1E-3	3.9E-3	0.54
PreMFunds	2.67	1.43	1.87
PreCash	-4.84	2.52	-0.92
PrePCs	-0.01	3.4E-4	-0.78
PreTrades	-0.05	0.22	-0.25
PreNAccts	0.13	0.35	0.37
CAServPre	1.03	0.60	1.71
FAServPre	-0.25	0.63	-0.40
MLServPre	-0.74	0.48	-1.53
ContPre	0.15	1.44	0.10
ProbPre	0.01	0.01	0.89
ServValPre	0.25	0.43	0.59

Table 23: Training using financial and behavioral variables (FAC_transfer group)

Coefficient Estimates			
Variable	**Estimate**	**Std.Err.**	**t-Statistic**
PreAssets	-0.00	1.1E-6	-1.88
PreDebt	1.26	1.20	1.05
PreEquity	-0.58	1.15	-0.50
PreFee	-0.00	5.2E-4	-0.00
PreFeebsd	-0.00	2.4E-6	-0.34
PreMargin	3.7E-4	1.3E-3	0.28
PreMFunds	-0.83	1.16	-0.71
PreCash	0.40	1.40	0.29
PrePCs	-0.00	1.7E-4	-1.42
PreTrades	0.14	0.09	1.58
PreNAccts	-0.06	0.16	-0.37
CAServPre	0.02	0.37	0.06
FAServPre	-0.49	0.42	-1.16
MLServPre	0.09	0.35	0.27
ContPre	0.17	0.83	0.20
ProbPre	-0.00	0.01	-0.25
ServValPre	0.11	0.30	0.36

Table 24: Training using financial and behavioral variables (FA_transfer group)

Coefficient Estimates			
Variable	**Estimate**	**Std.Err.**	**t-Statistic**
PreAssets	3.1E-6	1.0E-6	2.97
PreDebt	0.09	1.00	0.09
PreEquity	1.31	0.94	1.40
PreFee	-0.00	4.5E-4	-0.38
PreFeebsd	1.7E-6	2.4E-6	0.71
PreMargin	-0.00	1.2E-3	-0.38
PreMFunds	1.53	0.94	1.62
PreCash	0.95	1.25	0.76
PrePCs	2.8E-4	1.6E-4	1.78
PreTrades	-0.12	0.08	-1.49
PreNAccts	0.06	0.14	0.40
CAServPre	-0.40	0.33	-1.22
FAServPre	0.30	0.36	0.82
MLServPre	0.17	0.27	0.62
ContPre	-0.31	0.77	-0.40
ProbPre	-0.00	0.01	-0.35
ServValPre	-0.03	0.23	-0.12

Table 25: Training using financial and behavioral variables (no_transfer group)

Upon analyzing Tables 23, 24 and 25, a few conclusions can be drawn:

- As expected from the basic guidelines of Program Alpha, most FAs in the benchmark group base themselves on each client's `asset size` and `production credits` to determine whether to keep them in their books or transfer them out.
- As before, a large percentage of assets invested in mutual funds may have been a strong reason for transferring clients out, mostly to the call center.
- There exists some evidence that a significant share of the clients who were less satisfied with the service level being offered to them (low values of `FAServPre`, `CAServPre` and `MLServPre`) were transferred to another financial advisor or to the call center. The hypothetical explanation behind this factoid is that some FAs may have based their selections on the personal relationship they had with their clients, as it is likely that clients who are more satisfied with their FA would be more open to a closer and friendlier relationship.

Input Node – Logistic Regression (1)					
		Predicted			
		SN	*FAC*	*FA*	*Totals*
Observed	*SN*	675	6	9	690
	FAC	12	7	0	19
	FA	33	0	7	40
	Totals	720	13	16	749

	Observed			
	SN	*FAC*	*FA*	*Overall*
% Agree	*97.8%*	*36.8%*	*17.5%*	*92.0%*

Table 26: Training using financial and behavioral variables

Table 26 shows the training performance on the test data set of the first model generated by the logistic method. **Error! Reference source not found.** below shows the predicting performance of this model using the scoring data set of non-benchmark FAs. The scoring set contains 1,735 data points, which correspond to clients of weaker implementers of Program Alpha.

Input Node - Predict: Logistic Regression (11)					
		Predicted			
		SN	*FA*	*FAC*	*Totals*
Observed	*SN*	1546	45	19	1610
	FA	70	2	2	74
	FAC	49	1	1	51
	Totals	1665	48	22	1735

	Observed			
	SN	*FA*	*FAC*	*Overall*
% Agree	*96.0%*	*02.7%*	*02.0%*	*89.3%*

Table 27: Scoring of non-benchmark clients using financial and behavioral variables

Both the training and scoring parts of this approach have indicated very low fit and predictability levels, as observed during training and scoring phases, respectively. The small size of the data due to scarceness of complete data points (points containing full financial and behavioral data) drives this second model relatively insignificant from a statistical perspective. Therefore, no specific conclusions will be drawn regarding differences in client segmentation criteria between benchmark and non-benchmark FAs.

4.2.2 Preliminary Retention Test

A preliminary test was run to verify initial client response to the implementation of Program Alpha based on client retention. The test consisted of searching for a pattern that would possibly indicate why certain clients had closed their accounts after being transferred to another financial advisor or to the call center-based advisory division.

Logistic regression and classification tree algorithms were executed in order to generate models that expressed "Retention" as a function of other financial variables. For this test, behavioral client data was not available.

Table 28 contain a summary of the logistic regression.

Coefficient Estimates Call Center Transfer Clients			
Variable	**Estimate**	**Std.Err.**	**t-Statistic**
PreAssets	-0.01	6.9E-5	-7.20
PreEquity	0.98	0.49	1.99
PreFee	-0.00	1.9E-3	-0.26
PreFeebsd	1.3E-4	2.1E-4	0.65
PreMargin	-4.24	20.78	-0.20
PrePCs	1.3E-4	3.2E-4	0.41
PreTrades	-0.02	0.19	-0.13
PreNAccts	0.58	0.19	3.10

Clients transferred to another financial advisor

Coefficient Estimates FA Transfer Clients			
Variable	**Estimate**	**Std.Err.**	**t-Statistic**
PreAssets	4.7E-7	4.4E-7	1.09
PreEquity	-0.03	0.14	-0.25
PreFee	-0.00	5.7E-4	-1.72
PreFeebsd	-0.00	2.8E-6	-0.41
PreMargin	-0.00	7.9E-4	-0.84
PreMFunds	-0.33	0.11	-2.91
PrePCs	3.7E-5	1.1E-4	0.34
PreTrades	-0.19	0.04	-4.81

Clients transferred to call center

Table 28: Summary of logistic regression

Tables 29 and 30 contains a summary of the classification tree analysis.

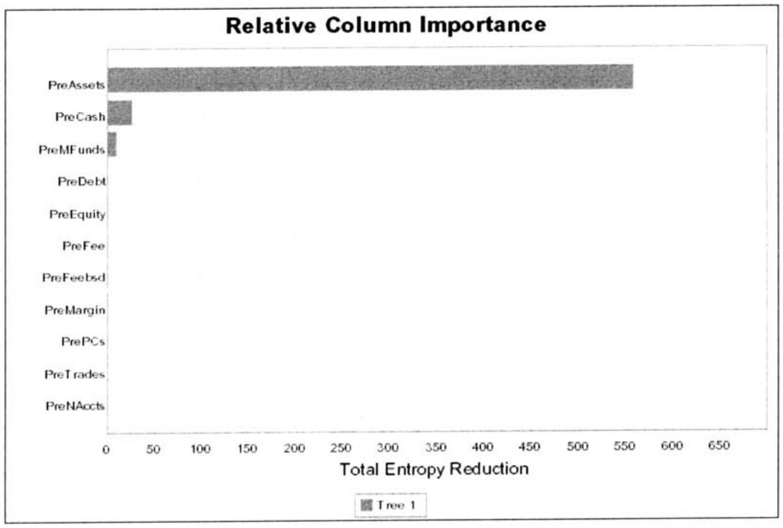


Table 29: Clients transferred to another FA

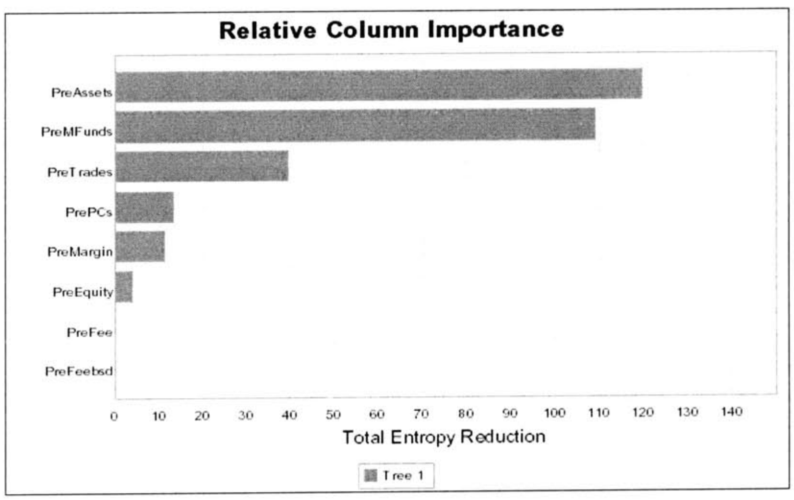


Table 30: Clients transferred to FAC

Upon analyzing Tables 29 and 30, a few conclusions can be drawn:

- In the case of clients transferred to another financial advisor, one can observe through the tables above that the variable *PreAssets* (account size) can almost completely explain certain accounts being closed. It is possible to notice, by inspecting the data, that the vast majority of accounts closed within this group were under a certain dollar size.

- Explaining the retention response of clients transferred to the call center is a more intricate task. From observing the analysis in the tables above, especially Table 24, the initial conclusion that can be drawn is that a large proportion of accounts closed were of individuals or households with a relatively small share of assets invested in mutual funds, as well as individuals or households with little trading activity throughout the year. The classification tree analysis also suggests that a significant share of clients with smaller account sizes may have also closed their accounts, although the logistic regression analysis did not indicate the same fact as strongly.

4.3 Conclusions

The following conclusions were drawn from the analyses performed in this chapter.

- It would not be possible to generate an actual formula for client segmentation for *Program Alpha* based on the data collected so far. The number of degrees of freedom (variables) in any analysis related to the topics here is very large and would require a much larger volume of FAs involved with the program in order to generate a data set that would carry statistically significant information. Nonetheless, the simplified analysis performed in this chapter sheds relevant, though preliminary, qualitative insight.
- The models presented in this section for explaining segmentation of clients to be kept in the books and clients to be transferred to FAC is quite robust.
- It is unquestionable that the most important segmentation criteria used by all FAs has been the dollar size of assets in each account (*PreAssets*), as well as the number of production credits (*PrePCs*) generated by each household.
- FAs considered less strong implementers of Program Alpha seem, for the most part, to agree with strong implementers on their segmentation criteria, with some potential differences in how they select clients to be transferred to the call center-based advisory division. Weaker implementers seem to have transferred more

clients to the call center than the stronger implementers would have in their places.

- There is some evidence that FAs may have transferred to the call center-based advisory division a significant share of clients who had a large percentage of assets invested in mutual funds.
- There is some evidence that clients with high trading activity were generally kept by the financial advisor, which is a conclusion highly correlated to the previous point.
- The vast majority of accounts closed by clients transferred to other FAs were very small accounts and there is no statistical evidence that the transfer process may have caused "good clients" to close their accounts. Most of the accounts closed were under $4,000.
- A large proportion of accounts closed by clients transferred to the call center were of individuals or households with a relatively small share of assets invested in *mutual funds*, as well as individuals or households with little *trading* activity throughout the year.

Most of the conclusions presented above are highly exploratory and preliminary, given the small size and relative sparseness of the data pool used in this analysis. However, the approach demonstrated in this chapter can be extended with the use of denser data sets to generate a very robust algorithm based on hard financial data, as well as soft attitudinal and behavioral statistics. Such algorithm could be generally applied to any client book and would help FAs just joining Program Alpha in segmenting their client base, at least from a high level, and beginning to make decisions regarding client migration to other FAs and FAC.

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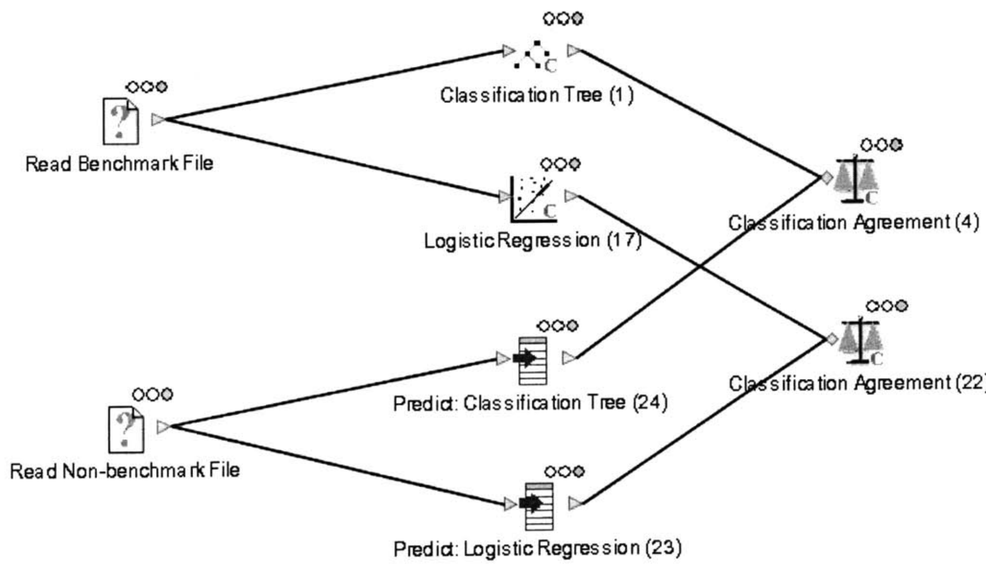
Appendix

Supervised Learning Model

The following model was generated in *Insightful Miner* for producing the output in section 3.1. Parameters of the model were changed throughout the analysis to focus on the appropriate combinations of dependent and independent variables.



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